



Research article

The impact of economic growth on environmental efficiency of the electricity sector: A hybrid window DEA methodology for the USA

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ARTICLE INFO

Article history:

Received 12 October 2017

Received in revised form

22 January 2018

Accepted 23 January 2018

Available online 7 February 2018

Keywords:

Efficiency

Electricity

Window DEA

N-shape

USA

ABSTRACT

This paper estimates the efficiency of the power generation sector in the USA by using Window Data Envelopment Analysis (W-DEA). We integrate radial and non-radial efficiency measurements in DEA using the hybrid measure while we extend the proposed model by considering good and undesirable outputs as separable and non separable. Then in the second stage, we perform parametric and non-parametric econometric techniques in order to model the relationship between the calculated environmental efficiencies and economic growth in attaining sustainability. Our empirical findings indicate a stable N-shape relationship between environmental efficiency and regional economic growth in the case of global and total pollutants but an inverted N-shape in the case of local pollutants. This implies that attention is required when considering local and global pollutants and the extracted environmental efficiency scores. A clear message to policy makers and government officials is that climate change which calls for economic, environmental and social concern should be analyzed according to its dispersion and regional dimension.

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1. Introduction

There is a general consensus among policy makers and government officials that electricity industry constitutes the largest emitting sector in the USA with a total carbon dioxide (CO₂) emissions amounting up to 2.2 billion metric tones in 2012 (IEA, 2014). It is noteworthy that at the end of 2012, power generation sector accounted for 31% (IEA, 2014) of total anthropogenic Greenhouse Gas Emissions (GHG).

Although there is a striking need for reducing emissions generated by the electricity sector to meet environmental goals, most of the existing studies focus mainly on the examination of the connection between environmental efficiency and economic growth known as Environmental Kuznets Curve (EKC) hypothesis, ignoring the role of the electricity sector (Managi, 2006; Daraio and Simar, 2005; Millimet et al., 2003; Zarzoso and Moranco, 2004; Zaim and Taskin, 2000; Taskin and Zaim, 2000).¹ On the other hand,

many empirical studies assess the efficiency of the electricity industry neglecting its role to the environmental degradation (see among others Goto and Tsutsui, 1998; Vaninsky, 2006; Kounetas, 2015). However, during the recent years, there are some attempts from the academic scholars to evaluate the efficiency of electricity industry integrating their greenhouse gas emissions (see for example Li et al., 2016; Chen et al., 2017; Monastyrnko, 2017). These studies, apply variants of the Data Envelopment Analysis (hereafter DEA) in order to captivate possible spillover effects. Although we examine the same relationship, we apply a different methodology which combines a novel window DEA (W-DEA) approach and non-parametric panel data estimations.

DEA method can be used for the evaluation of a decision making unit (DMU) efficiency relative to other DMUs. DEA has been used in calculating relative efficiencies in various applications (see for example Han et al., 2018; Frija et al., 2011; Sueyoshi, 1999; Larsson and Telle, 2008; Hoang and Alauddin, 2012; Halkos and Managi, 2017). In this study, we estimate the efficiency of the electricity sector through the methodology of a non-parametric “mathematical” approach (DEA), originally developed by Farrell (1957). The DEA, method given the data set, produces a frontier that is optimal, while it represents the maximum output available for any DMU in the study, for its given inputs (Webb, 2003). Given that the non-

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¹ EKC hypothesis implies a non linear relationship of an inverted ‘U’ type between environmental degradation and economic growth.

parametric frontier estimation does not require the imposition of any specific production technology, this is a standard approach in studies of transition and emerging economies, where assumptions of competitive markets with cost-minimization may not be appropriate (Apergis and Polemis, 2016).

The majority of the existing studies devoted on testing an EKC hypothesis estimate reduced-form equations that enter the model either in a parametric (piecewise linear, quadratic, cubic models) or in a nonparametric form (i.e. semiparametric, partially linear models, etc).² More specifically, Millimet et al. (2003) explore the significance of modeling policies when calculating the association between emissions-income. Similarly to our study, they use USA state-level panel data on two air pollutants (NO_x and SO₂) in order to estimate several EKCs by comparing parametric and semi-parametric techniques. They argue in favor of the more flexible semiparametric approach confirming the hypothesis of an inverted U-shape between emissions and regional economic growth.

Other researchers (see for example Bruyn and Opschoor, 1997; Sengupta, 1997) claim that some indicators such as CO₂ emissions exhibit an N-shape, implying that the environmental damage starts rising again after a fall to a specific point. Lastly, in an interesting paper, Maddison, 2006 extends the notion of the EKC nexus by estimating a spatial panel data model of 135 OECD countries in order to capture the effect of economic growth on several air pollutants (SO₂, NO_x, CO and VOC emissions). The study, concludes that national SO₂ and NO_x emissions are strongly affected by the per capita emissions of neighbor countries.

On the other hand, relatively few empirical studies adopt a simultaneous equations system in order to address the impact of economic growth on environmental degradation. In the seminal paper of Dean's (2002), a panel simultaneous equations system is built around a Heckscher-Ohlin model capturing thus certain effects of trade liberalization on the environmental quality (water pollution). The sample included 28 Chinese provinces over the period 1987–1995 and the empirical findings suggest that there is a direct negative trade effect on environmental damage which is fully reversed when the income growth is taken into account. In a more recent paper, Jayanthakumaran and Liu (2012) try to assess the relationship in China between trade, growth and emissions using provincial panel data for water and air pollution over the period 1990–2007. They use a variety of econometric techniques ranging from a quadratic log function specification to a simultaneous equations system similar to Dean's approach. The major contribution of this paper was to shed light on the empirical evidence for both the EKC and the trade related emissions hypothesis. Their findings are rather mixed providing little support in favor of the EKC hypothesis.

The objective of this study is to estimate the regional efficiency scores of the electricity sector in a large scale economy such as the USA by combining separable and non-separable inputs in the production process to generate good and undesirable outputs respectively. Based on these estimates, we attempt to draw sharp inferences about the shape of the EKC by utilizing parametric and non-parametric panel data techniques.

The contribution of our paper is three-fold. First, it goes beyond the existing literature in that it uses a micro level dataset originated from nearly 789 power plants on 50 US regions (states). Second, it utilizes a W-DEA approach with certain innovations such as the radial and non-radial efficiency measurements and the treatment of inputs and outputs (good and undesirable) as separable and non-separable. Although there are few similar studies that take into

account the time series or dynamics into DEA modeling (see for example Asmild et al., 2004; Halkos and Tzeremes, 2009; Tone and Tsutsui, 2010; Wang et al., 2013; Khalili-Damghani et al., 2015), our study is the first which uses W-DEA methodology along with parametric and non-parametric econometric techniques. In our empirical analysis and for this balanced panel data a dynamic analysis based window DEA is used. If instead a cross sectional based static DEA was used all adjustment to any shock takes place within the same time period in which this occurs. This is justified only if we have either an equilibrium relationship or if the adjustment processes are really very fast (Perman and Stern, 1999).

Third, and most importantly, the paper concurs that there is a stable N-shaped relationship between environmental efficiency (in each of the three pollution models) and regional economic growth. Taken together, this set of findings is important in that it provides some useful policy implications towards the abatement of air pollution in order to achieve sustainability. The rest of the paper is organized as follows. Section 2 introduces the data and describes the methodology, while Section 3 discusses the empirical findings. Finally, Section 4 concludes the paper while reports some policy implications.

2. Data and methodology

In order to estimate electricity efficiency, we use the utilization of net capacity (UNC) as a proxy for good output, while three undesirable outputs accounting for CO₂, SO₂ and NO_x emissions are incorporated in our analysis.³ The inputs in the production process are total energy transmission, as a proxy for capital and total operating cost, as a proxy for labor. The latter combines expenses of labor, materials, depreciation, and several other cost components, while the former captures all electricity losses that occur between the points of generation (power plants) and the transportation and distribution of electricity through high and low voltage power grids (infrastructure) to final consumers (Vaninsky, 2006).

In contrast, many studies (Färe et al., 1989a, b, 1996, 2004; Färe and Grosskopf, 2003, 2004; Chung et al., 1997; Tyteca, 1996, 1997; Taskin and Zaim, 2001; Zofio and Prieto, 2001; Zaim, 2004; Managi, 2006; Yoruk and Zaim, 2006; Picazo-Tadeo and Garcia-Reche, 2007; Picazo-Tadeo et al., 2012; Zhang et al., 2011) use the capital stock and since they do not have available data on a regional basis, they often incorporate the perpetual inventory method taking into account a uniform depreciation rate $\delta = 6\%$.⁴ However, since capital stock includes several capital assets (i.e. transportation, machinery, buildings, etc) a uniform depreciation rate seems unrealistic. Our proposed method deals with this issue by taking into account its proxy variable (i.e. energy transmission) which varies across different power plants.

Moreover, we assume that the two inputs affect the good output in a separable way since neither energy transmission nor operating cost of a power plant are linked with its production process (net generation). In contrast, the production of the good output generates the air pollutants distorting the environmental conditions in a non-separable way.

2.1. Descriptive statistics

All the above variables are obtained by the Energy Information

² For a survey of the EKCs on an empirical and theoretical perspective see the relevant studies of Dinda (2004) and Kijima et al. (2010) respectively. For a piecewise linear approximation in DEA models see Cook and Zhu (2009).

³ Utilization of net capacity is given by $UNC = \frac{\text{Net Generation}}{\text{Summer+Winter Peak Demand}}$.

⁴ This method calculates the capital stock as: $K_t = I_t + (1 - \delta)K_{t-1}$ where K_t is the state's gross capital stock in current year; K_{t-1} is the state's gross capital stock in the previous year; I_t is the state's gross fixed capital formation and δ is the depreciation rate.

Table 1
Descriptive statistics.

Statistical measures	Undesirable Outputs			Good output	Inputs		Income variable
	CO ₂	SO ₂	NO _x	Net Capacity	Energy Transmission	Total Cost	Real GDP/capita
Observations	650	650	650	650	650	650	650
Mean	48,322,510.000	171,634.000	75,344.130	1638.537	4,750,821.000	82,019.660	45,498.860
Median	38,227,289.000	83,359.500	60,693.500	1561.284	3,184,037.000	42,547.000	44,055.000
Maximum	267,000,000.000	1,152,407.000	510,931.000	137,366.7	27,299,280.000	1,321,369.000	70,918.000
Minimum	6583.000	28.000	409.000	−0.007	1151.000	94.000	28,957.000
Standard deviation	45,569,866.000	219,004.300	70,755.920	5403.526	5,139,173.000	137,111.200	8373.095
Skewness	2.128	2.008	1.832	24.43581	1.871	5.284	0.726
Kurtosis	9.744	7.167	7.503	614.324	6.500	39.750	3.232
Coefficient of variation	0.943	1.276	0.939	3.298	1.082	1.672	0.184
Jarque-Bera	1722.461	907.063	912.638	10,186,188	710.967	39,602.000	58.612
P-value (Jarque-Bera)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Administration (EIA), while per capita real GDP (in 2009 prices) by state is drawn from the Regional Economic Accounts of the Bureau of Economic Analysis.⁵ Data are collected for a sample of 650 observations, relative to primarily annual information from EIA energy statements of an unbalanced micro panel of nearly 789 electric utilities operating in 50 US states spanning the period 2000 to 2012. The choice of the time period is dictated strictly by data availability.

Descriptive statistics for the model variables are portrayed in Table 1. From the diagnostics used in this analysis, it is clear that there is a limited variability in relation to the mean except for the net capacity (good output) where the coefficient of variation exceeds one. However, from the relative values of the skewness and kurtosis we argue that the variables do not follow the normal distribution. This is also confirmed by the Jarque-Bera statistic in which the null hypothesis is strongly rejected in all of the cases indicating that the variables do not follow the normal (Gaussian) distribution.

2.2. The radial separable DEA

The main problem in applying DEA in the presence of undesirable outputs is that efficiency is attained by minimizing inputs and maximizing outputs. But in the case of undesirable outputs we may wish to maintain same inputs with more good output and less undesirable output. Thus undesirable outputs demand a special treatment in model formulations (Cook et al., 2015).

Koopmans (1951) mentioned that some undesirable outputs like pollutant emissions and wastes disposal affect negatively the environment and should be reduced. In these lines Färe et al. (1989a, b) differentiated outputs as desirable (good) and undesirable outputs and suggested a non-linear programming model in calculating DMUs efficiencies in the presence of both desirable and undesirable outputs. Since then several scholars have proposed efficiency measurements in the case of undesirable outputs (see for example Anderson and Philpott, 2002).

One way to tackle this problem is to shift undesirable outputs into inputs and apply DEA (Hoang and Coelli, 2011). Seiford and Zhu (2002) provided radial measures assuming efficiency may be improved by increasing good and decrease undesirable outputs simultaneously. For doing so he proposed a multiplication of undesirable outputs by −1 and with the use of an adequate translation vector to transform all negative undesirable outputs to be positive. These two transformations of changing position and translation provide the same efficient frontiers (Scheel, 2001) with the Seiford and Zhu method to be valid in the case of variable returns to scale

(VRS) and the two methods to provide different inefficiency scores.

Another way is to empower undesirable output and to consider it as a good output. Färe et al. (1989a, b) treated good and undesirable outputs asymmetrically measuring environmental technology in a production function setup with the use of distance functions non-parametrically. At the same time by imposing strong and weak disposability they calculated environmental performance indicators. It is true that there is a dispute between using the assumption of weak or strong disposability (Dakpo et al., 2016; Rødseth, 2016; Finn, 2017; Wang et al., 2017). Tackling undesirable outputs the adoption of the two available hypotheses of strong and weak disposability affects seriously DMUs' efficiencies. A production function reveals strong disposability of undesirable outputs if these are freely disposable. On the other hand the weak disposability corresponds to pollutants' reductions associated with lower production of desirable outputs assuming as mentioned certain costs. More specifically, some of the undesirable outputs like CO₂ emissions cannot be reduced using the existing available technologies and can be considered as "Null-Joint outputs" as defined in Färe and Grosskopf (2004) and the reduction of CO₂ emissions will be associated with a reduction in the amount of electricity produced. As some CO₂ emissions unavoidably will be produced if electricity is generated then the weak disposability assumption is adequate. In contrast, some undesirable outputs like SO_x and NO_x emissions can be cleared out. This disposal will be at a cost that will be done with an increase in the production cost. A coal fired power plant may reduce SO₂ emissions by switching to low (or free) sulphur content fuels or by installing abatement methods like flue gas desulphurization with a typical expected abatement efficiency of 90%. This abatement entails some input costs (or output reduction) but not necessarily at the cost of abating 90% of the produced electricity (depending on the installed abatement method). In such a case the Null-Joint relation is broken and the weak disposability assumption becomes inadequate. As mentioned in the previous comment, in our case having no information on abatement we rely on the weak disposability assumption.

Similarly, Yang and Pollitt (2009, 2010), proposed a model that distinguishes weak and strong disposability assumptions among various undesirable outputs based on their respective technical features. The empirical findings indicate that imposing the technically correct disposability features on undesirable outputs makes a significant difference to the final efficiency evaluation. This suggests the necessity of properly distinguishing disposability features among undesirable outputs in a production process. As Cooper et al. (2007) point out a drawback of radial models is that they disregard slacks when dealing with undesirable outputs slacks are not accounted in the efficiency measurement.

It is interesting to note that in a recent study, Pérez et al., 2017 present an analysis of energy efficiency and of greenhouse gas

⁵ Similarly to Halkos and Tzeremes (2013) we excluded the state of District Columbia (DC) that acted as a potential outlier.

emissions in the Chilean manufacturing industry by region and sector using DEA models. This study, develops three alternative ways to handle and compare undesirable outputs, while the source of inefficiency in each DMU is calculated using scale efficiency, and the evolution over time is analyzed using the Malmquist index.

The radial method is applied in Charnes, Cooper and Rhodes (CCR) and Banker, Charnes and Cooper (BCC) models with ignorance of non-radial input and output slacks.⁶ Similarly the non-radial method of slack based method copes with slacks but it ignores the radial inputs and outputs. To tackle this problem we integrate radial and non-radial efficiency measurements in DEA using the hybrid measure while we extend the proposed model by considering inputs and good and undesirable outputs as separable and non separable.⁷ If n , γ and s correspond to the number of DMUs, inputs and outputs and $X \in R^{\gamma \times n}$ and $Y \in R^{s \times n}$ the observed input and output data matrices then the decomposition of radial and non-radial parts of inputs and outputs $X^R \in R^{\gamma_1 \times n}$, $X^{NR} \in R^{\gamma_2 \times n}$ with $\gamma = \gamma_1 + \gamma_2$ and $Y^R \in R^{s_1 \times n}$, $Y^{NR} \in R^{s_2 \times n}$ with $s = s_1 + s_2$ may be expressed as follows:

$$X = \begin{pmatrix} X^R \\ X^{NR} \end{pmatrix} \quad Y = \begin{pmatrix} Y^R \\ Y^{NR} \end{pmatrix} \quad (1)$$

Assuming a positive data set with $X, Y > 0$ the production possibility set P and for a constant returns to scale formulation is expressed as:⁸

$$P = \{x, y\} | x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\} \quad (2)$$

For a specific $DMU_0(x_0, y_0) = DMU_0(x_0, y_0) = (x_0^R, x_0^{NR}, y_0^R, y_0^{NR}) \in P$ we have

$$\begin{aligned} \alpha x_0^R &= X^R \lambda + s^{R-} \\ x_0^{NR} &= X^{NR} \lambda + s^{NR-} \\ \zeta y_0^R &= Y^R \lambda - s^{R+} \\ y_0^{NR} &= Y^{NR} \lambda - s^{NR+} \end{aligned} \quad (3)$$

With $\alpha \leq 1$, $\zeta \geq 1$, and $\lambda, s^{R-}, s^{NR-}, s^{R+}, s^{NR+} \geq 0$. The slacks are represented by the vectors $s^{R-} \in R^{\gamma_1}$ and $s^{NR-} \in R^{\gamma_2}$ corresponding to the excesses for the radial and non-radial inputs and $s^{R+} \in R^{s_1}$ and $s^{NR+} \in R^{s_2}$ for the losses of the radial and non-radial outputs.

Following Cooper et al. (2007) a feasible expression is with $\alpha = 1$, $\zeta = 1$, $\lambda_0 \geq 1$, $\lambda_j = 0$ and with zero slacks. An index ρ is defined as

$$\rho = \frac{1 - \frac{\gamma_1}{\gamma}(1 - \alpha) - \frac{1}{\gamma} \sum_{i=1}^{\gamma_2} \frac{s_i^{NR-}}{x_{i0}^{NR}}}{1 + \frac{s_1}{s}(\zeta - 1) + \frac{1}{s} \sum_{k=1}^{s_2} \frac{s_k^{NR+}}{y_{k0}^{NR}}}, \quad (4)$$

Then $DMU_0(x_0, y_0)$ is hybrid efficient if $\alpha = 1$, $\zeta = 1$, $s^{NR-} = 0$, $s^{NR+} = 0$.

⁶ See Charnes et al. (1978) and Banker et al. (1984) respectively.

⁷ Hybrid was proposed in Tone (2004). For an application of a hybrid optimization algorithm in attaining sustainability see Gonzalez et al., 2011.

⁸ To test for returns to scale we use the proposed method by Simar and Wilson (2002) and compute the DEA efficiency scores under the CRS and VRS assumption. Specifically we test the results obtained from CRS against VRS as: $H_0: E^0$ is CRS vs $H_1: E^0$ is VRS. With the test statistic given by as: $T(X_n) = \frac{1}{n} \sum_{i=1}^n \frac{E_{CRS,n}(X_i, Y_i)}{E_{VRS,n}(X_i, Y_i)}$. Relying on the method proposed by Simar and Wilson (2002) and in our case the p-value of the test is $0.79 > 0.05$ (with 2000 bootstrap replications) and we cannot reject the null hypothesis of constant returns to scale (CRS).

At this moment suppose we have n DMUs using γ inputs and producing a good and an undesirable output. With the vectors of inputs, and of good and undesirable outputs being $x \in R^\gamma$, $y^G \in R^{s_1}$ and $y^B \in R^{s_2}$ respectively and with the matrices $X = [x_1, \dots, x_n] \in R^{\gamma \times n}$, $Y^G = [y_1^G, \dots, y_n^G] \in R^{s_1 \times n}$ and $Y^B = [y_1^B, \dots, y_n^B] \in R^{s_2 \times n}$ then assuming $X, Y^G, Y^B > 0$ the production possibility set is presented as

$$P = \{x, y^G, y^B\} | x \geq X\lambda, y^G \leq Y^G \lambda, y^B \geq Y^B \lambda, \lambda \geq 0\} \quad (5)$$

and a $DMU_0(x_0, y_0^G, y_0^B)$ is efficient in the case of undesirable outputs if there is not any vector $(x, y^G, y^B) \in P$ with at least one strict inequality and $x_0 \geq x$, $y_0^G \leq y^G$, $y_0^B \geq y^B$. In this case we have the following expression:

$$\rho^* = \min \frac{1 - \frac{1}{\gamma} \sum_{i=1}^{\gamma} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left(\left(\sum_{k=1}^{s_1} \frac{s_k^G}{y_{k0}^G} + \sum_{k=1}^{s_2} \frac{s_k^B}{y_{k0}^B} \right) \right)} \quad (6)$$

$$\begin{aligned} \text{Subject to} \quad & x_0 = X\lambda + s^- \\ & x_0^G = X^G \lambda - s^G \\ & y_0^B = Y^B \lambda + s^B. \\ & s^- \geq 0, s^G \geq 0, s^B \geq 0, \lambda \geq 0. \end{aligned} \quad (7)$$

Now, the vectors $s^- \in R^\gamma$ represent the excesses in inputs, $s^B \in R^{s_2}$ in undesirable outputs and $s^G \in R^{s_1}$ the losses in good outputs.

At this time it is worth considering that environmental undesirable outputs like pollutants emissions are not separable from the associated desirable output and a reduction in undesirable outputs comes together with a reduction in the desirable output. There is an inseparability issue between undesirable outputs and good outputs but possibly also certain inputs. In this case we separate the set of outputs (Y^G, Y^B) into separable good (Y^{SG}) and non separable good and undesirable outputs (Y^{NSG}, Y^{NSB}) . The same applies also to the inputs (X^S, X^{NS}) with the case of separable inputs being $X^S \in R^{\gamma_1 \times n}$ and non separable $X^{NS} \in R^{\gamma_2 \times n}$. Although for the case of separable good outputs (Y^{SG}) we have the same form of production as Y^G in P , in the case of non separable outputs (Y^{NSG}, Y^{NSB}) we have:

$$\begin{aligned} P_{NS} = \{ & (X^S, X^{NS}, Y^{SG}, Y^{NSG}, Y^{NSB}) | x^S \geq X^S \lambda, x^{NS} \geq X^{NS} \lambda, y^{SG} \\ & \leq Y^{SG} \lambda, y^{NSG} \leq Y^{NSG} \lambda, y^{NSB} \geq Y^{NSB} \lambda, \lambda \geq 0\} \end{aligned} \quad (8)$$

and a $DMU_0(x_0^S, x_0^{NS}, y_0^{SG}, y_0^{NSG}, y_0^{NSB})$ is non separable efficient if for any μ ($0 \leq \mu \leq 1$) $(x_0^S, x_0^{NS}, y_0^{SG}, \mu y_0^{NSG}, \mu y_0^{NSB}) \notin P_{NS}$ and together with at least one strict inequality $x_0^S \geq x^S$, $x_0^{NS} \geq x^{NS}$, $y_0^{SG} \leq y^{SG}$, $y_0^{NSG} = y^{NSG}$, $y_0^{NSB} = y^{NSB}$. In this case the corresponding hybrid model can be expressed as:

$$\rho^* = \min \frac{1 - \frac{1}{\gamma} \sum_{i=1}^{\gamma_1} \frac{s_i^-}{x_{i0}^S} - \frac{\gamma_2}{\gamma} (1 - \mu)}{1 + \frac{1}{s} \left(\left(\sum_{k=1}^{s_1} \frac{s_k^G}{y_{k0}^{SG}} + (s_{21} + s_{22})(1 - \mu) \right) \right)} \quad (9)$$

$$\begin{aligned}
\text{Subject to } & X_0^S = X_S \lambda + s^{S-} \\
& \mu X_0^{NS} = X_{NS} \lambda \\
& Y_0^{S_G} = Y_{S_G} \lambda + s^{S_G-} \\
& \mu Y_0^{NS_G} \leq Y_{NS_G} \lambda \\
& \mu Y_0^{NS_B} \leq Y_{NS_B} \lambda \\
& s^{S-} \geq 0, s^{S_G-} \geq 0, \lambda \geq 0, 0 \leq \mu \leq 1
\end{aligned} \quad (10)$$

2.3. The proposed model for measuring environmental efficiency

DEA window analysis was proposed by Charnes et al. (1985) dealing with panel data and relying on the principle of moving average. In this analysis each DMU is considered as a different DMU and every DMU's performance is compared both with the performance of the other DMUs and with its own performance through time. To perform a DEA window analysis in the case of N DMUs ($n = 1, 2, \dots, N$) using γ inputs and δ outputs in T time periods ($t = 1, 2, \dots, T$) this will produce a sample of $N \times T$ observations where an observation n in period t (DMU_n^t) has an γ dimensional input vector x_n^t and an s dimensional output vector y_n^t of the form

$$x_n^t = \begin{bmatrix} x_n^{1t} \\ \vdots \\ x_n^{\gamma t} \end{bmatrix} \quad y_n^t = \begin{bmatrix} y_n^{1t} \\ \vdots \\ y_n^{st} \end{bmatrix} \quad (11)$$

If the window begins at time v ($1 \leq v \leq T$) with a width equal to w ($1 \leq w \leq T-v$) then the inputs and outputs matrices can be presented as

$$\begin{aligned}
x_{vw} &= \begin{bmatrix} x_1^v & x_2^v & \dots & x_N^v \\ x_1^{v+1} & x_2^{v+1} & \dots & x_N^{v+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{v+w} & x_2^{v+w} & \dots & x_N^{v+w} \end{bmatrix} \\
y_{vw} &= \begin{bmatrix} y_1^v & y_2^v & \dots & y_N^v \\ y_1^{v+1} & y_2^{v+1} & \dots & y_N^{v+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{v+w} & y_2^{v+w} & \dots & y_N^{v+w} \end{bmatrix}
\end{aligned} \quad (12)$$

The substitution of inputs and outputs in the appropriate model specifications as in the CCR and BCC models provide us with the DEA window analysis results.

The measurement of DMUs' environmental performance using DEA window analysis relies on the calculation of an indicator of the ratio of the quantity index of good output to a quantity of an index of an undesirable output (among others, Färe et al., 1999, 2000; Zaim et al., 2001; Zaim, 2004). The higher this indicator (ratio of good to undesirable output) the higher is the DMU's environmental performance.

Considering N DMUs (in our case 50 USA states), each producing s outputs using γ inputs then efficiency is calculated as:

$$f_m = \sum_{i=1}^s b_{im} y_{im} / \sum_{j=1}^{\gamma} c_{jm} x_{jm} \quad (13)$$

where y_{im} (>0) is the amount of output i by the m th DMU, x_{jm} (>0) is the amount of input j used by the m th DMUs, b_{im} and c_{jm} are the weights (or multipliers) for the output and the input respectively. The efficiency ratio (13) is maximised subject to the constraints:

$$\sum_{i=1}^s b_{im} y_{im} / \sum_{j=1}^{\gamma} c_{jm} x_{jm} \leq 1 \quad \text{for } m = 1, \dots, N \quad (14)$$

and

$$b_{im}, c_{jm} \geq 0 \quad (15)$$

For the estimation of efficiency changes through time DEA window analysis is applied relying on the idea of a moving average of appropriate width. In this way DMUs are treated as different in each time period. That is, in our case the DMUs are the 50 USA states ($N = 50$) over a time period of 13 years period ($t = 13$) and with the imposition of a 3-year ($w = 3$) window. The fact that there are no technical changes within each of the windows because all DMUs in each window are compared against each other and in order for the results to be credible a narrow window width must be used (see for instance Asmild et al., 2004). As such in our analysis a 3 year window has been chosen ($w = 3$). Then each DMU is placed in the window treated as different DMU for each of the three years (the width of the window). Therefore in our case the first window contains the years 2000, 2001, 2002. This in fact increases the DMU numbers under examination from 789 electric utilities to 2367 ($n \times w = 789 \times 3$) and therefore the analysis is performed to these DMUs. The window then moves on one year period and the analysis is performed on the next three year set, dropping the original year and adding a new year. As a result, the next three year analysis will include the years 2001, 2002 and 2003. In other words, each DMU is allocated in the window and it is treated as a different DMU for each of the three years of each window. This leads to a number of windows (nw) equal to 11 ($t-w+1$) and a number of 1650 different DMUs ($N \times w \times nw = 50 \times 3 \times 11$). The process starts from window 1 (including years 2000, 2001 and 2002) and ends to the last (11th) window (containing years 2010, 2011 and 2012) and having analyzed in total 1650 different DMUs.

It is worth mentioning that the frontier derived from starting three years (i.e 2000, 2001 and 2002) window observations represents the average technology of the specific years which usually lacks of comparability with the technology detected through the ending three years (i.e 2010, 2011 and 2012), since during this long period, the operational and abatement technologies might have changed significantly for the USA power generation units. This outcome justifies the adoption of weak disposability assumption with reducing undesirable outputs being not possible without assuming certain costs (Zofio and Prieto, 2001). For instance, a power plant burning fossil fuels produces electricity (good output) and emits sulphur dioxide emissions; under weak disposability a 20% sulphur emissions reduction is feasible if it is associated with a 20% reduction in electricity output with the input vector remaining constant (Färe and Primont, 1995).⁹

2.4. Econometric framework

In order to capture the effect of per capita economic growth on environmental efficiency levels we have used three parametric and one nonparametric approach. First, similarly to many empirical

⁹ A coal fired power plant may reduce SO₂ emissions by switching to low (or free) sulphur content fuels or by installing abatement methods like coal washing, sorbent injection or flue gas desulphurization with a typical expected abatement efficiency of 25%, 80% and 90% respectively. This abatement entails some input costs (or output reduction) but not necessarily at the cost of abating 25%, 80% or 90% of the produced electricity (depending on the installed abatement method). In such a case the weak disposability assumption may be inappropriate but having no information on abatement we rely on the weak disposability assumption.

studies (see for example Millimet et al., 2003; Jayanthakumaran and Liu, 2012), we estimate a two-way OLS fixed-effects panel data model (basic model) using a cubic specification of the following form:¹⁰

$$EFF_{it} = \alpha_i + \beta_t + b_0 + b_1 GDP_{it} + b_2 GDP_{it}^2 + b_3 GDP_{it}^3 + \varepsilon_{it} \quad (16)$$

$i = 1, 2, \dots, 50$ and $t = 1, 2, \dots, 13$

where EFF_{it} is a vector that includes CO₂ efficiency scores, SO₂ and NO_x efficiency scores and finally CO₂, SO₂ and NO_x efficiency scores for state i at time t , α_i and β_t are state and time fixed effects used in order to capture common factors across the cross-section element. GDP_{it} is real GDP (in constant 2009 prices) per capita for state i at time t and ε_{it} are zero mean i.i.d. innovations.¹¹

It is worth mentioning that endogeneity could be raised as a result of the use of the polynomial GDP per capita. If this happens then, an OLS estimator that is used in order to measure the impact of income growth on electricity efficiency scores could be biased (Hausman and Ros, 2013). For this reason, we re-estimate our basic model by applying two dynamic GMM estimators known as DIF-GMM and SYS-GMM developed by Arellano and Bond (1991) and Blundell and Bond (1998) respectively.¹²

It is worth mentioning that most of the empirical studies assume specific functional forms for their regression relationships. This means that they employ parametric regression models. This could be a problem since parametric models raise misspecification concerns in terms of their functional forms (Tran and Tsionas, 2010). In order to deal with this issue, we rely on panel data nonparametric methodology where little prior restriction is imposed on the model's structure. In this way, we do not have to assume a priori any functional relationship between the electricity efficiency and the level of regional per capita growth. The nonparametric local polynomial smoothing model (LPOLSM) can be written as:

$$EFF_{it} = \alpha_i + \beta_t + g(gdp_{it}) + u_{it} \quad (17)$$

$i = 1, 2, \dots, 50$ and $t = 1, 2, \dots, 13$

where $g(\cdot)$ is an unknown function, u_{it} is a mean zero residual assumed to be uncorrelated with $g(\cdot)$, α_i are state fixed effects, and finally β_t are time effects. As it is stated, one of the main advantage of the LPOLSM is that it does not dictate a priori a specific functional form compared to the parametric regressions models (Seifert and Gasser, 2006). The local polynomial estimator of g at a point x_0 is based on a polynomial approximation of $g(GDP)$ near x_0 by minimizing the following formula:¹³

$$\sum_{i=1}^n \left(EFF_i - \sum_{j=0}^p \beta_j (GDP_i - x_0)^j \right)^2 K \left(\frac{GDP_i - x_0}{h} \right) \quad (18)$$

¹⁰ Before conducting the econometric estimations we have investigated the stationarity properties of the sample variables and concluded that all the variables are integrated of order one (I-1) and cointegrated by using "second generation" unit root tests due to the presence of cross-section dependence (Pesaran, 2004). To preserve space the relevant results are available from the authors upon request.

¹¹ It is worth mentioning that the basic parametric regression model does not consider other factors like technological innovation and trade activity which are also important factors that affect the environmental efficiency. However, due to serious data restrictions the inclusion of the aforementioned covariates were not feasible.

¹² Another reason that justifies the use of the DIF-GMM estimator is that the latter performs well for $N > T$ which is the case in our data (Arellano and Bond, 1991).

¹³ For simplicity reasons we only keep subscript i and omit t .

Subject to $\beta = (\beta_0, \dots, \beta_p)'$.

where $K(\cdot)$ is a kernel (nonnegative symmetric weight) function and $h = h_n$ is the bandwidth smoothing parameter for sample size n chosen by cross validation (see for example Brockmann et al., 1993; Fan and Gijbels, 1995 for details). In this case, we could estimate $g(x_0)$ using a local polynomial of the following form:

$$\sum_{j=0}^p \hat{\beta}_j (x - x_0)^j \quad \text{at } x = x_0 \quad (19)$$

Therefore the local polynomial estimator is given by the following equation:

$$\hat{g}(x_0) = \hat{\beta}_0. \quad (20)$$

3. Results and discussion

Table 2 presents the results of the regional environmental efficiency estimates as derived from our hybrid model broken down by three pollution models.¹⁴ The efficiency results reveal that in all of the specifications, 4 out of 50 states (Alaska, Hawaii, Utah and Wyoming) are reported to be environmentally efficient in terms of the anthropogenic emissions since their scores are close to unity. On the other hand, 5 out of 50 states report the lowest efficiency values ranging from 0.002 to 0.394. These are Rhode Island, Delaware, New Jersey, Illinois and Ohio.

In terms of the static analysis, the descriptive statistics reveal low disparities of regional environmental efficiencies among USA states since the standard deviation and the coefficient of variation (CV) appear to be relatively low ranging from 0.164 to 0.198 and 0.317 to 0.907 respectively. Moreover, on average terms USA states have an environmental efficiency level ranging from 0.218 to 0.516. This means that USA regions on average terms are able to reduce their total CO₂, SO₂ and NO_x levels generated by the electricity sector (see Model 1) by 78.2% to reach the efficiency frontier, while also increase their regional economic growth (proxied by per capita GDP) by the same proportion.¹⁵

In terms of the time series analysis and for Model 1 (see Fig. 1A in the Appendix), the average annual efficiency scores of electricity sector in each state relative to the state's frontier reveal stability or a slight general improvement for the cases of Alaska, Hawaii, Utah, New Mexico, North Dakota and Wyoming and a slight decline in overall efficiency levels for the cases of California, Delaware, Florida, Georgia, and Texas. The states with the highest mean efficiency scores are Alaska and Hawaii with 93.2% and 80.5% respectively, while the states with the lowest values are Maryland (5%) and Ohio (5.1%). It is worth mentioning that similar results are obtained in the other two specifications (see Figures A2 and A3).

Lastly, our findings are on average terms in alignment with the study of Halkos and Tzeremes (2013) who estimate the efficiency scores for the US states for the year 2005. However, the DEA efficiency scores obtained in this paper are much larger (0.516 in Model 3) than the aforementioned study in which the mean value of the estimated conditional environmental efficiency is 0.2933

¹⁴ To preserve space, we only report the efficiency scores for the latest available year (2012). The detailed results over the whole examination period are available upon request.

¹⁵ Since the mean environmental efficiency score for the extended (full) model equals to 0.218 or 21.8%, the rest amount 0.782 (78.2%) denotes the inefficiency score.

Table 2
Efficiency scores in each of the three models (2012).

State	Model 1 (CO ₂ + SO ₂ + NO _x)	Model 2 (SO ₂ + NO _x)	Model 3 (CO ₂)
Alaska	0.909	0.909	0.907
Alabama	0.125	0.163	0.548
Arkansas	0.173	0.196	0.527
Arizona	0.149	0.205	0.541
California	0.075	0.097	0.306
Colorado	0.182	0.210	0.492
Connecticut	0.123	0.193	0.511
Delaware	0.021	0.066	0.337
Florida	0.072	0.143	0.419
Georgia	0.059	0.090	0.366
Hawaii	0.849	0.867	1.000
Iowa	0.414	0.424	0.687
Idaho	0.371	0.366	0.379
Illinois	0.044	0.172	0.512
Indiana	0.213	0.260	0.581
Kansas	0.207	0.231	0.563
Kentucky	0.176	0.203	0.571
Louisiana	0.467	0.450	0.790
Massachusetts	0.103	0.167	0.509
Maryland	0.094	0.143	0.438
Maine	0.188	0.259	0.500
Michigan	0.114	0.162	0.514
Minnesota	0.164	0.195	0.397
Missouri	0.111	0.135	0.530
Mississippi	0.154	0.167	0.463
Montana	0.177	0.276	0.562
North Carolina	0.092	0.133	0.363
North Dakota	0.369	0.361	0.649
Nebraska	0.243	0.259	0.576
New Hampshire	0.259	0.300	0.514
New Jersey	0.031	0.102	0.312
New Mexico	0.498	0.533	0.730
Nevada	0.295	0.432	0.685
New York	0.107	0.155	0.360
Ohio	0.077	0.104	0.394
Oklahoma	0.139	0.162	0.459
Oregon	0.125	0.141	0.229
Pennsylvania	0.117	0.179	0.504
Rhode Island	0.002	0.002	0.434
South Carolina	0.122	0.190	0.545
South Dakota	0.461	0.442	0.518
Tennessee	0.045	0.102	0.367
Texas	0.060	0.117	0.504
Utah	0.634	0.725	0.824
Virginia	0.158	0.176	0.452
Vermont	0.219	0.217	0.254
Washington	0.153	0.187	0.247
Wisconsin	0.240	0.267	0.586
West Virginia	0.152	0.364	0.538
Wyoming	0.561	0.682	0.821
Descriptives			
Mean	0.218	0.262	0.516
Stdev	0.198	0.195	0.164
Median	0.153	0.194	0.511
Max	0.909	0.909	1.000
Min	0.002	0.002	0.229
CV	0.907	0.744	0.317

with a high standard deviation (0.2339 compared to 0.164). This discrepancy, could be attributed to the different methodology applied since the former study uses a conditional directional distance function estimator extending the model of Kuosmanen (2005) ignoring the role of separability in the input-output analysis.

Next we perform various econometric techniques in order to model the relationship between the calculated environmental efficiencies and economic growth in attaining sustainability. In the first stage, we perform parametric regression analysis by estimating three cubic model specifications.

The results from our analysis are depicted in Table 3. Specifically,

in two of the three estimated models, we find significant evidence consistent with an N-shaped relationship between environmental efficiency and regional economic growth. More specifically, the coefficients on the GDP terms (i.e. income, income squared and income cubed) in the first two models (Model 1 and 2) are statistically significant alternating their signs starting from positive to negative. This suggests the existence of N-shaped curve. However, for the CO₂ model, the individual estimates are not statistically significant although the pattern of alternating signs still holds. It is worth mentioning that the existence of non linear effects generated by a cubic and not a quadratic specification is justified under the likelihood ratio tests (LR) testing the restrictions that the extra polynomial terms (e.g. GDP² and GDP³) are zero (H₀: b₂ = b₃ = 0). As it is evident in all of the three models, the LR tests, reject the null hypothesis under which the restricted model is nested to the unrestricted one (third degree polynomial model).

Since we have an N-shaped curve, we have two estimated turning points representing an estimated peak and an estimated low (Kijima et al., 2010). More specifically, the estimated peak in all of the three models range from 21,233 US dollars (in 2009 constant prices) to 42,549 US dollars, while the estimated low of the curve lies within the boundary of 59,956 to 82,627 US dollars. These values are on average in alignment with other studies such as Halkos and Tzeremes (2013) who estimate a turning point equal to approximately 49,000 US dollars confirming however -by the implementation of non-parametric analysis- the existence of an inverted U-shaped curve. We must stress however, that our findings contradict the study of Millimet et al. (2003) who argue that an inverted U shaped curve is evident for the USA states with a cubic specification model prevailing in their parametric analysis. Their estimated peak equals to 8657 US dollars (in 1987 price levels) for the full sample model (NO_x model) and becomes 10,570 US dollars (for the partial NO_x sample model) and 16,417 US dollars (for the partial SO₂ sample model) respectively.

The estimated equations in the cubic specifications appear to be well behaved to the diagnostic tests. However, the Wooldridge F-tests for first order autocorrelation in the error term (W-T diagnostic test) denote the existence of autocorrelation revealing that the error terms in all of the three models are not i.i.d, meaning that the errors display serial dependence.

Having estimated the cubic models and in order to account for possible endogeneity issues generated by the inclusion of income as dependent variable into our specifications, we utilise three dynamic DIF-GMM models. The results are also reported in Table 3 (Panel B). As it may be seen, the empirical evidence in favor of an N-shaped curve does not dramatically change when employing a dynamic panel analysis. More specifically, the income polynomial coefficients (i.e. GDP, GDP squared and GDP cubed) are statistically different from zero at the p < 0.01 level of significance in the first two models and at the p < 0.05 level of significance in the last model including only CO₂ emissions.

For all of the three models, b₁s and b₃s are positive while b₂s are negative (alternating signs) suggesting the existence of a stable N-shaped relationship between environmental efficiency and regional economic growth. Additionally, the lagged efficiency score indicators are in nearly all cases significant at the 1% level and their high magnitude implies the suitability of the dynamic panel data estimation. Regarding the magnitude of the estimated two turning points, it is noteworthy that they depict less variability compared to the cubic models. Moreover, the Sargan-Hansen test fails to reject the null hypothesis in all of the three models implying that the instruments used in the empirical estimation are valid (Arellano, 2003; Roodman, 2009). In addition, from the p-values of the first and second order autocorrelation (AR1 and AR2) it is assumed that the error terms are independent over time allowing for the

Table 3
Parametric regression results.

Control variables	Model 1 <i>Dependent variable: EFF (CO₂ + SO₂ + NO_x)</i>	Model 2 <i>Dependent variable: EFF (SO₂ + NO_x)</i>	Model 3 <i>Dependent variable: EFF (CO₂)</i>
Panel A - OLS Cubic Specification			
GDP	0.0001* (1.53)	0.00013* (1.41)	0.00007 (1.00)
GDP ²	−2.96E−09* (−1.56)	−2.66E−09* (−1.46)	−1.47E−09 (−1.02)
GDP ³	1.90E−14* (1.58)	1.73E−14* (1.49)	9.36E−15 (1.03)
Constant	−2.244*** (−2.74)	−1.865** (−2.35)	−0.650 (−0.94)
<i>Diagnostics</i>			
Observations	600	600	600
Shape of curve	N-shape	N-shape	N-shape
Estimated Peak	21,233	42,549	36,612
Estimated Low	82,627	59,956	68,089
F-test	11.26*** [0.00]	12.46*** [0.00]	16.18*** [0.00]
W-T	3.39* [0.07]	5.06*** [0.03]	7.35*** [0.01]
LR	3.71** [0.06]	3.95*** [0.07]	3.02* [0.08]
Panel B - DIF-GMM Specification			
EFF (−1)	0.565*** (11.28)	0.419*** (67.20)	0.242*** (4.70)
EFF (−2)	−0.094** (−2.03)	0.162*** (60.94)	0.031 (0.81)
GDP	0.0003*** (2.58)	0.0001*** (9.20)	0.00015*** (1.90)
GDP ²	−5.65E−09*** (−2.62)	−2.30E−09*** (−9.57)	−3.15E−09** (−1.94)
GDP ³	3.59E−14*** (2.64)	1.42E−14*** (9.95)	2.07E−14*** (2.00)
Constant	−4.538*** (−2.44)	−1.888*** (−8.23)	−2.112* (−1.54)
<i>Diagnostics</i>			
Observations	500	500	500
Shape of curve	N-shape	N-shape	N-shape
Estimated Peak	42,776	44,327	44,402
Estimated Low	62,145	63,654	57,047
Instruments	67	69	69
Sargan-Hansen test	46.25 [0.82]	48.98 [0.84]	45.07 [0.92]
AR(1)	−2.58*** [0.009]	−2.63*** [0.008]	−2.88*** [0.004]
AR(2)	0.51 [0.60]	−1.13 [0.26]	−1.60 [0.11]
Panel C - SYS-GMM Specification			
EFF (−1)	0.495*** (47.05)	0.534*** (89.58)	0.445*** (85.77)
EFF (−2)	0.122*** (71.33)	0.137*** (47.92)	−0.080*** (−42.75)
GDP	0.0002*** (25.85)	−0.00003*** (−2.55)	0.0002*** (14.69)
GDP ²	−4.23E−09*** (−29.38)	4.98E−10** (2.22)	−5.09E−09*** (−15.01)
GDP ³	2.86E−14*** (33.26)	−2.38E−15* (−1.70)	3.28E−14*** (15.40)
Constant	−3.019*** (−22.07)	0.648*** (3.28)	−3.790*** (−13.29)
<i>Diagnostics</i>			
Observations	550	550	550
Shape of curve	N-shape	Inverted N-shape	N-shape
Estimated Peak	39,323	95,498	26,366
Estimated Low	59,279	43,997	77,090
Instruments	80	80	80
Sargan-Hansen test	47.61 [0.98]	48.00 [0.97]	44.11 [0.98]
AR(1)	−2.92*** [0.00]	−2.54*** [0.01]	−2.90*** [0.00]
AR(2)	−0.05 [0.95]	0.54 [0.58]	0.04 [0.97]

Note: The use of the fixed effects is justified after a Hausman test for each of the three models. Robust z-statistics/t-statistics are in parentheses. The numbers in square brackets denote the p-values. LR denotes the Likelihood Ratio test for the presence of non-linear effects. W-T is the Wooldridge F-test for first order autocorrelation in the error term. AR(1) and AR(2) are tests for serial autocorrelation. Significant at ***1%, **5% and *10% respectively. The estimated peaks and lows are in US dollars at 2009 prices. To preserve space and for the sake of simplicity we do not report the estimates of the time dummies which are available by the authors on request. The lag selection was performed relying on AIC and SC criteria.

estimates to be consistent.

In the next step and in order to perform a sensitivity analysis, we employ the SYS-GMM estimator. The main reason for using the latter is that it increases efficiency in cases where the lagged dependent variables are poor instruments for the first-differenced regressors improving the accuracy of the estimates dramatically (Blundell and Bond, 2000). For all the above reasons, we re-estimate our three models and the results are reported in Table 3 (see Panel C). As it is evident, the results support the previous empirical findings in two out of three models (see Model 1 and Model 3) leading to the confirmation of an N-shaped curve. Surprisingly, when SO₂ and NO_x emissions are the only air pollutants in our econometric model, the N-shaped curve does not hold since the income polynomial coefficients come with the opposite sign sequence (i.e from negative to positive and then to negative).

In order to avoid to assume a specific functional form for the regression relationships and to empirically test the validity of our

findings, we adopt a nonparametric LPOLSM to capture the impact of regional income growth on environmental efficiency in the US states over the scrutinised period. The graphical presentation of the non parametric estimation of $g(\cdot)$ in each of the three models (i.e all gases included, only SO₂ and NO_x and finally only CO₂ emissions) along with the 95% confidence bands (CI) is portrayed in Figs. 1–3. It is evident that the relationship between GDP/capita (expressed in natural logarithm) and environmental efficiency is nonlinear exhibiting a strong similar N-shaped pattern.

From the inspection of Fig. 1, we argue that there is an increasing nonparametric regression line up to a certain logged GDP level (10.5). This indicates that when regional income level increase up to that point regions' environmental efficiencies levels are also increasing (i.e. regions' environmental inefficiency decreases). However after that estimated peak ("turning point") it is evident that the regression line slightly decreases up to a certain point (10.8) and increases henceforth. This means that within this closed

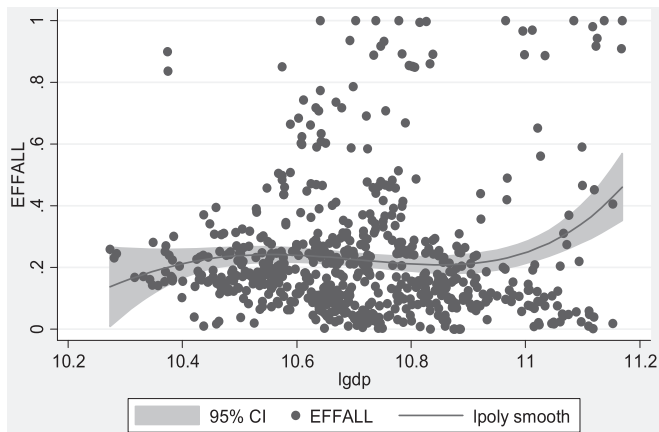


Fig. 1. Local polynomial smooth for Model 1.

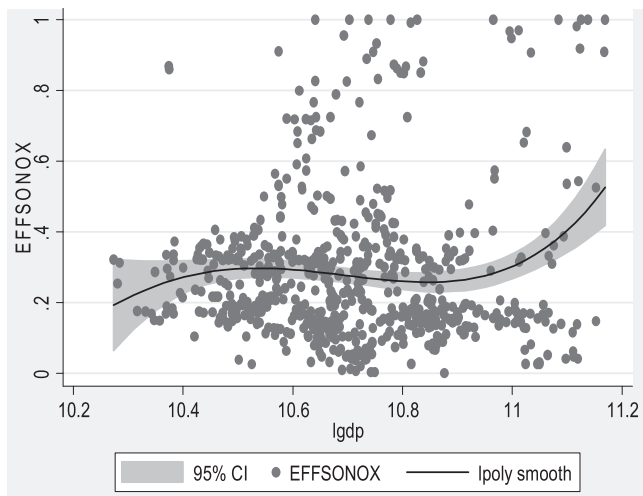
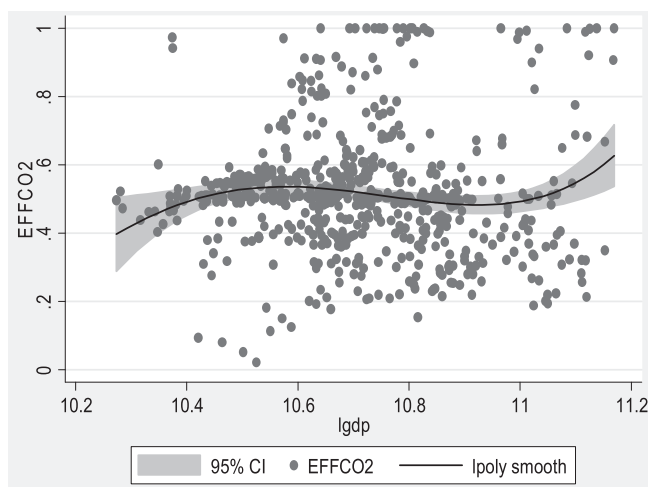


Fig. 2. Local polynomial smooth for Model 2.



Note: In all figures solid lines denote the local polynomial estimated smooth, while the grey area depicts the 95% confidence bands. We chose Epanechnikov kernel function and the degree of the polynomial smooth is set to three.

Fig. 3. Local polynomial smooth for Model 3. Note: In all figures solid lines denote the local polynomial estimated smooth, while the grey area depicts the 95% confidence bands. We chose Epanechnikov kernel function and the degree of the polynomial smooth is set to three.

interval, the logged GDP/capita has a negative impact on USA states environmental efficiency levels. Alternatively, the regions' environmental inefficiency levels are increasing. From the combined analysis of these findings, we argue that there is an N-shaped relationship between regional environmental efficiency and regions' logged GDP/capita levels. This pattern is also evident in the other two models (see Figs. 2 and 3). Similarly to Halkos and Tzeremes (2013), it appears that for a large part of logged GDP/capita (i.e. > 60,000 \$) the effect of regions' GDP on their environmental efficiency levels is neutral, indicating that after a certain point region's economic growth does not influence its environmental performance.

Based on the aforementioned findings, we argue that the factors causing an inverted U-shape pattern are various. Among them improvement in environmental quality due to production technological mode, exportation of "dirty industry" to less develop or developing countries, the role of preferences and regulation on the emissions profile of polluters. Pollution will stop increasing and start to decrease with economic growth because some constraints will become non-binding (Lieb, 2003). In analyzing long time-series, the three effects in continuation lead to an initial stage of economic development with a negative environmental effect due to scale effect followed up by structural changes in the economy as well as in the production methods that take place at the next stages of development which have positive effects on the environment and are due to composition and technical effects. Lieb (2003) claims that the downturn part of the N-shape may be justified by a shock while the upturn part due to an equilibrium relationship. The final upturn of the extracted N-shape curve may be justified by the completion of the internalization of the pollution externality as well as that the abatement opportunities are exhausted.

4. Conclusions and policy implications

In our study the efficiency of the power generation sector in the USA states is estimated by integrating radial and non-radial efficiency measurements in a W-DEA framework. Specifically, using the proposed hybrid measure we consider first inputs and good and undesirable outputs as separable and non-separable. Then we perform various parametric and non parametric econometric techniques to model the relationship between the extracted environmental efficiencies and economic growth in accomplishing sustainability. Our empirical results present initially an N-shape relationship between environmental efficiency (in all specifications) and regional economic growth.

The use of appropriate econometric methods in the second stage is important. In the presence of local (sulphur and nitrogen) and global (carbon) pollutants the estimated shapes of the curves differ. Specifically, in the case of local pollutants we extract an inverted N shape curve (only in SYS-GMM) while in the case of global pollutants an N-shape curve is evident. When considering all pollutants together an N-shape curve is derived due to dominance of CO₂ emissions. This N-shape curve has the estimated peak at \$39,323 and the estimated low at \$56,279. This findings reveals that the decline in environmental harm due to economic growth may be short-term and pollutants' emissions will be raised for an indefinite period above the income level of \$56,279. The econometric findings indicate that the USA regions on average are able to reduce their total CO₂, SO₂ and NO_x levels generated by the electricity sector by 78.2% to reach the efficiency frontier, while also increase their regional economic growth (proxied by per capita GDP) by the same proportion. Moreover, the estimated average annual efficiency scores in each state reveal a general stability or a slight general improvement for the states of Alaska, Hawaii, Utah, New Mexico, North Dakota and Wyoming. On the contrary, there is a slight

decline in overall efficiency levels in regions such as California, Delaware, Florida, Georgia, and Texas. The states with the highest average efficiency scores are Alaska and Hawaii with 93.2% and 80.5% respectively, while the states with the lowest values are Maryland (5%) and Ohio (5.1%).

An important feature of this study is that it incorporated the amount of global and local pollutants as undesirable outputs. Based upon our DEA results, we suggest that electric power plants should strategically invest on clean coal technology in such a way that they can attain the improvement in not only their operational efficiencies but also on environmental scale merits. As clearly suggested by Sueyoshi and Goto (2013), the above strategy is practical and beneficial in both regulated and deregulated USA states since such an investment cost can be recovered either by the regulated electricity tariffs or the ability to pay by the consumers who are environmentally aware.

These findings could be important for policy makers, academic researchers and government officials. More specifically, they call for the need to strengthen the effectiveness of environmental degradation policies by ensuring sustainability of the electricity sector in order to drastically reduce emissions. Moreover, policy makers and government officials have to stimulate investments in productive sectors like the energy sector and more likely to promote the use of Renewable Energy Sources. This can be accompanied by pursuing more financial resources for Research and Development and more cost effective mitigation methods. Moreover, we argue that the USA regions (states) must increase their installed renewable energy capacity in order to align with federal environmental goals achieving more efficient energy use among the USA periphery. Lastly, one important policy implication worth mentioning is that in such analyses careful attention to pollutants examined is needed. Particularly, pollutants should be analyzed according to their dispersion and regional dimension avoiding their simultaneous consideration in cases of calculating environmental efficiencies.

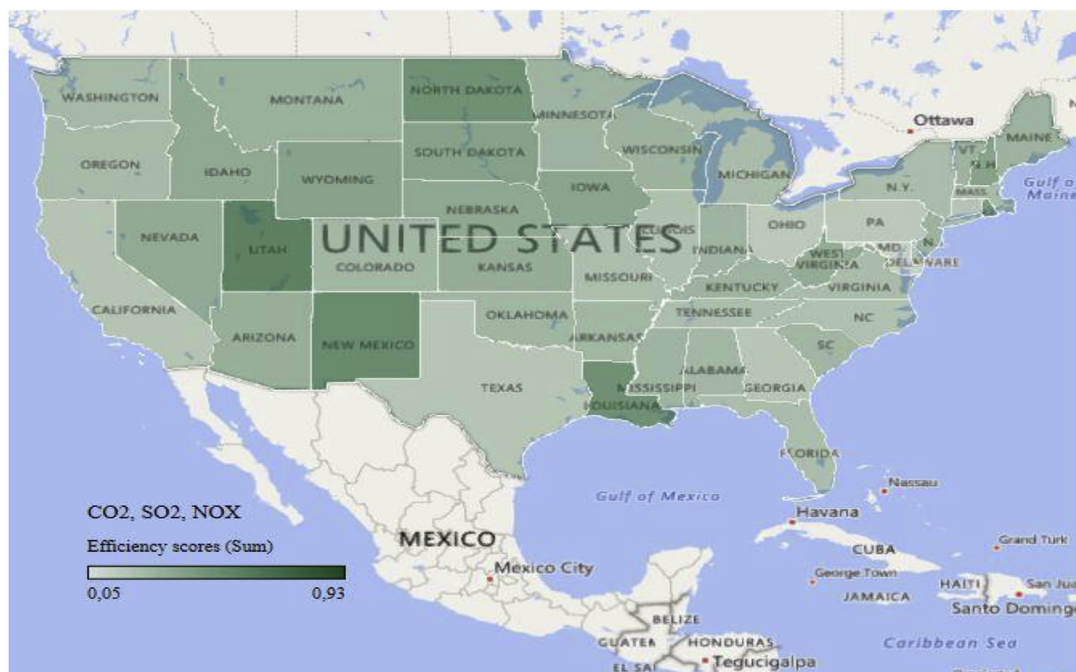
Finally we would like to mention possible directions for further research. A logical extension may well be the application to a

sample containing other cross-section elements (i.e EU regions) with data in different time periods in order to capture the dynamic effects involved in the examined relationship. Moreover, researchers may focus on the examination of possible thresholds that split the sample data into different policy regimes. Another alley for future research may be to include spatial aspects such as geographical proximity and transportation cost in order to uncover possible regional differences and the sources of these different patterns. In addition to the above methodological issues, we need to deepen our research efforts toward more managerial aspects of the DEA efficiency scores measurement. One example is related with the investigation of the nature of the relationship between investment activity for environmental protection and the level of environmental efficiency.

Acknowledgments

The authors wish to express their gratitude to the Co-Editor-in-Chief Dr Jason Michael Evans and three anonymous referees of this journal for their fruitful comments and suggestions that substantially enhanced the merit of the paper. They also thank the Organizational Committee of the 23rd Annual Conference of the European Association of Environmental and Resource Economists (EAERE) which was held in Athens (June 28 June – 1 July 2017). An earlier version of this paper was also presented in Montpellier during the 1st International Conference on Energy, Finance and the Macroeconomy (ICEFM) organized by the Montpellier Business School (November 22–24, 2017). Special acknowledgements should be given to participants of the conferences for their useful contribution. All remaining errors remain with the authors. The usual disclaimer applies.

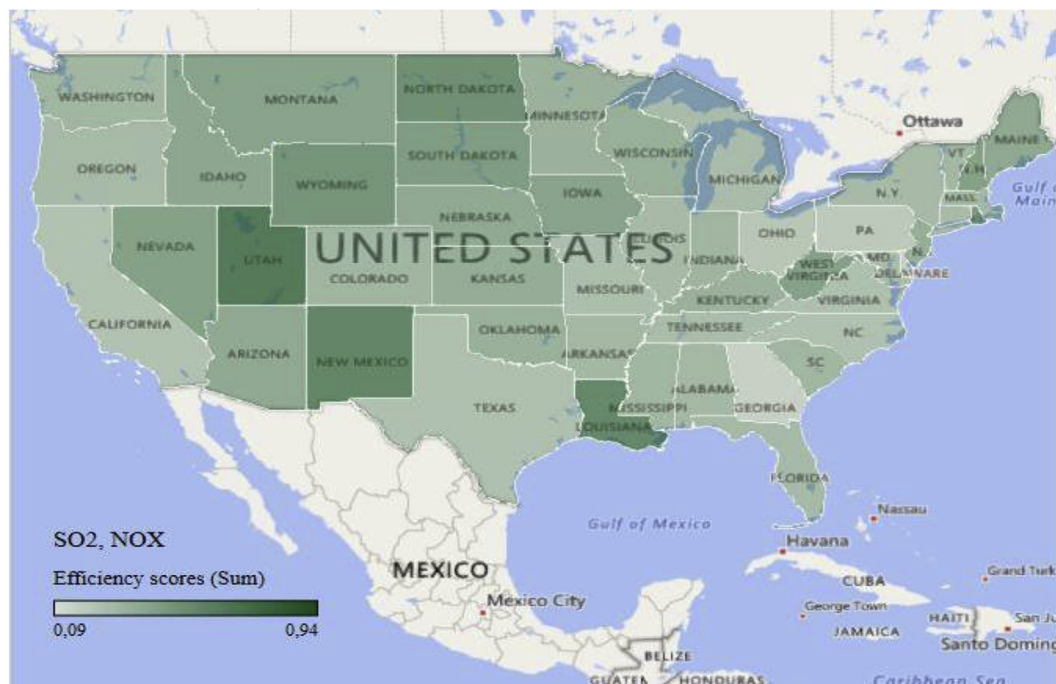
Appendix



Note: The figure reports the mean efficiency scores by state over the period (2000–2012). The efficiency scores were estimated with the window data envelopment analysis (hybrid method) considering inputs and outputs as separable and non separable. The benchmark best practice frontier for DEA is efficiency equal to 1.000.

Fig. 1A. : DEA efficiency scores for CO₂, SO₂, NO_x per US state.

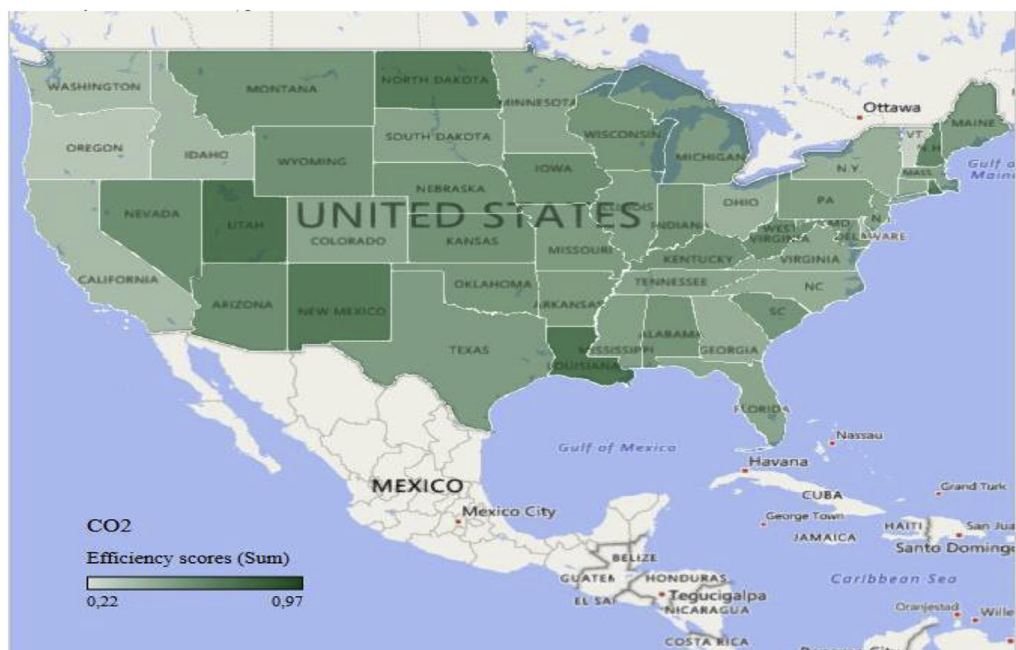
Source: Authors' elaboration.



Note: The figure reports the mean efficiency scores by state over the period (2000–2012). The efficiency scores were estimated with the window data envelopment analysis (hybrid method) considering inputs and outputs as separable and non separable. The benchmark best practice frontier for DEA is efficiency equal to 1.000.

Fig. 2A. DEA efficiency scores for SO₂, NO_x per US state.

Source: Authors' elaboration.



Note: The figure reports the mean efficiency scores by state over the period (2000–2012). The efficiency scores were estimated with the window data envelopment analysis (hybrid method) considering inputs and outputs as separable and non separable. The benchmark best practice frontier for DEA is efficiency equal to 1.000.

Fig. 3A. DEA efficiency scores for CO₂ per US state.

Source: Authors' elaboration.

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